Preliminary Numerical Experiments in Multiobjective Optimization of a Metallurgical Production Process

Bogdan Filipič and Tea Tušar
Department of Intelligent Systems
Jožef Stefan Institute
Jamova 39, SI-1000 Ljubljana, Slovenia
E-mail: bogdan.filipic@ijs.si, tea.tusar@ijs.si

Erkki Laitinen
Department of Mathematical Sciences
University of Oulu
P.O. Box 3000, FIN-90014 Oulu, Finland
E-mail: erkki.laitinen@oulu.fi

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This paper reports on preliminary numerical experiments in optimizing coolant flows in continuous casting of steel with respect to multiple objectives. For this purpose, Differential Evolution for Multiobjective Optimization (DEMO) coupled with a reliable numerical simulator of the casting process was applied. The algorithm parameters were initially tuned to balance between the quality of the expected results and the computational cost of the optimization process. Afterwards, suitable sets of coolant flow settings were calculated under conflicting requirements for minimum temperature deviations and predefined core length in the caster. In contrast to solutions produced in single-objective optimization, approximation sets of Pareto optimal fronts obtained in multiobjective optimization provide more information to metallurgists and allow for better insight into the casting process.

Povzetek: Članek obravnava nastavljanje pretokov hladila v industrijskem kontinuiranem ulivanju jekla kot večkriterijski optimizacijski problem in ga rešuje z evolucijskim algoritmom DEMO.

1 Introduction

Production and processing of materials are nowadays under strong market-driven pressure for shortening the process development time, reducing experimental costs, improving material properties, and increasing productivity. In achieving these goals, numerical analysis is playing an increasingly important role. Material scientists and engineers actually consider empirical knowledge and computational approximation as the basis for material process design and control. Numerical simulators give insight into process evolution, allow for execution of virtual experiments and support manual optimization by trial and error. However, the optimization procedure can be automated by coupling a simulator with an optimization algorithm and introducing a quality function which allows for automatic assessment of the simulation results.

Continuous casting of steel is an example of a process to which novel computational approaches have been applied intensively over the last years to enhance product characteristics and minimize production costs. In this complex metallurgical process molten steel is cooled and shaped into semi-manufactures. To cast high quality steel, it is important to properly control the metal flow and heat transfer during the process. They depend on numerous parameters, including the casting temperature, casting speed and coolant flows. Finding optimal values of process parameters is difficult as the number of possible parameter settings is high, the involved criteria are often conflicting, and parameter tuning through real-world experimentation is not feasible because of safety risk and high costs. Techniques applied to overcome these difficulties include knowledge-based techniques, neural networks, fuzzy logic and evolutionary computation. Nevertheless, the predominant optimization approach taken in the applied studies so far was to aggregate multiple criteria into a single cost value and solve the optimization problem empirically using the simulator-optimizer coupling.

In this paper we report on preliminary numerical experiments in optimizing secondary coolant flows on a steel casting machine with respect to multiple objectives and under technological constraints. The experiments were performed using a novel multiobjective optimization evolutionary algorithm, while in the underlying numerical simulations continuous casting of a selected steel grade under steady-state conditions was assumed. Through the obtained approximation sets of optimal solutions the plant engineers can get better insight into process behavior and parameter effects.

The paper outlines the related work, describes the optimization task and the multiobjective optimization approach, and reports on the performed numerical experiments and obtained results.

2 Related Work

Over the last years, several advanced computer techniques have been used in attempts to enhance the process performance and material properties in metallurgical production. Cheung and Garcia [3], for example, combine a numerical model of the process with an artificial intelligence heuristic search technique linked to a knowledge base to find parameters values that result in defect-free billet production. Chakraborti and coworkers [1] report that genetic algorithms have proved to be the most suitable for optimizing the settings of the continuous casting mold. They use a Pareto-converging genetic algorithm to solve a multiobjective problem of setting the casting velocity in the mold region. In a further study [2] relying on heat transfer modeling, genetic algorithms are used to determine the maximum casting speed and solidified shell thickness at the mold exit. Oduguwa and Roy [13] use a novel fuzzy fitness evaluation in evolutionary optimization and apply it in rod rolling optimization. They solve a multi-objective problem of optimal rod shape design.

Our approach to process parameter optimization in continuous casting of steel involves a numerical simulator of the casting process and various stochastic optimization techniques among which evolutionary algorithms play the key role. The initial version of the optimization system [11] was designed to search for process parameter values that would result in as high as possible quality of continuously cast steel. Based on empirical metallurgical criteria, it was able to deliver improved parameter settings that proved beneficial in practice. However, using a simple evolutionary algorithm, it spent thousands of process simulations to find high-quality solutions. As the time aspect is critical, the purpose of further exploration [9, 7] was to reduce the number of needed process simulations. These applied studies were all using the weighted-sum technique of aggregating multiple criteria into a scalar cost function. As opposed to that, in a recent work [10] an attempt was made to handle multiple criteria by means of evolutionary multiobjective optimization. Based on the initial findings, this paper refines the problem definition by introducing an additional technological constraint, justifies the algorithm settings by checking the algorithm performance metrics and analyzes the new numerical results.

3 Problem Description

In industrial continuous casting, liquid steel is poured into a bottomless mold which is cooled with internal water flow. The cooling in the mold extracts heat from the molten steel and initiates the formation of a solid shell. The shell formation is crucial for the support of the slab behind the mold exit. The slab then enters the secondary cooling area in which it is cooled by water sprays. The secondary cooling region is divided into cooling zones where the amount of the cooling water can be controlled separately.

We consider a casting machine with the secondary cooling area divided into nine zones. In each zone, cooling water is dispersed to the slab at the center and corner positions. Target temperatures are specified for the slab center and corner in every zone. Water flows should be tuned in such a way that the resulting slab surface temperatures match the target temperatures as closely as possible. From metallurgical practice this is known to reduce cracks and inhomogeneities in the structure of the cast steel. Formally, cost function c_1 is introduced to measure deviations of actual temperatures from the target ones:

$$c_1 = \sum_{i=1}^{N_\mathrm{Z}} |T_i^{\mathrm{center}} - T_i^{\mathrm{center}*}| + \sum_{i=1}^{N_\mathrm{Z}} |T_i^{\mathrm{corner}} - T_i^{\mathrm{corner}*}|, \tag{1}$$

where N_Z denotes the number of zones, T_i^{center} and T_i^{corner} the slab center and corner temperatures in zone i, and $T_i^{\mathrm{center}*}$ and $T_i^{\mathrm{corner}*}$ the respective target temperatures in zone i.

There is also a requirement for core length, l^{core}, which is the distance between the mold exit and the point of complete solidification of the slab. The target value for the core length, $l^{\mathrm{core}*}$, is prespecified, and the actual core length should be as close to it as possible. Shorter core length may result in unwanted deformations of the slab as it solidifies too early, while longer core length may threaten the process safety. We formally treat this requirement as cost function c_2:

$$c_2 = |l^{\mathrm{core}} - l^{\mathrm{core}*}|. \tag{2}$$

The optimization task is to minimize both c_1 and c_1 over possible cooling patterns (water flow settings). It is known that the two objectives are conflicting, hence it is reasonable to handle this optimization problem as a multiobjective one.

In search for solutions, water flows cannot be set arbitrarily, but according to the technological constraints. For each zone, minimum and maximum values are prescribed for the center and corner water flows. Moreover, to avoid unacceptable deviations of the core length from the target value, a hard constraint is imposed: $c_2 \leq \Delta l_{\max}^{\mathrm{core}}$. Candidate solutions not satisfying the water flow constraint and/or the core length constraint are considered infeasible.

A prerequisite for optimization of this process is an accurate numerical simulator, capable of calculating the temperature field in the slab as a function of process parameters and evaluating it with respect to cost functions (1) and (2).

For this purpose we used the mathematical model of the process with Finite Element Method (FEM) discretization of the temperature field and the corresponding nonlinear equations solved with relaxation iterative methods, already applied in previous single-objective optimization study of the casting process [8].

4 Multiobjective Optimization

4.1 Preliminaries

The multiobjective optimization problem (MOP) is defined as finding the minimum of the cost function $\mathbf{c}$:

$$\mathbf{c}\colon X \to Z$$
$$\mathbf{c}\colon (x_1, \ldots, x_n) \mapsto (c_1(x_1, \ldots, x_n), \ldots, c_m(x_1, \ldots, x_n)),$$

where X is an n-dimensional decision space, and $Z \subseteq \mathbb{R}^m$ is an m-dimensional objective space ($m \geq 2$). The objective vectors from Z can be partially ordered using the concept of *Pareto dominance*: $\mathbf{z}^1$ *dominates* $\mathbf{z}^2$ ($\mathbf{z}^1 \prec \mathbf{z}^2$) iff $\mathbf{z}^1$ is not worse than $\mathbf{z}^2$ in all objectives and better in at least one objective. When the objectives are conflicting, there exists a set of optimal objective vectors called *Pareto optimal front*. Each vector from the Pareto optimal front represents a different trade-off between the objectives and without additional information no vector can be preferred to another.

With a multiobjective optimizer we search for an *approximation set* that approximates the Pareto optimal front as well as possible. When solving MOPs in practice it is often important to provide the user with a diverse choice of trade-offs. Therefore, beside including vectors close to the Pareto optimal front, the approximation set should also contain near-optimal vectors that are as distinct as possible.

4.2 The DEMO Algorithm

Finding a good approximation set in a single run requires a population-based method. Consequently, evolutionary algorithms have been frequently used as multiobjective optimizers [4]. Among them, the recently proposed Differential Evolution for Multiobjective Optimization (DEMO) [15] is applied in optimizing the described metallurgical process.

DEMO is based on Differential Evolution (DE) [14], an evolutionary algorithm for single-objective optimization that has proved to be very successful in solving numerical optimization problems. In DE, each solution is encoded as an n-dimensional vector. New solutions, also called candidates, are constructed using operations such as vector addition and scalar multiplication. After the creation of a candidate, the candidate is compared with its parent and the best of them remains in the population, while the other one is discarded.

Because the objective space in MOPs is multidimensional, DE needs to be modified to deal with multiple objectives. DEMO is a modification of DE with a particular mechanism for deciding which solution should remain in the population. For each parent in the population, DEMO constructs the candidate solution using DE. If the candidate dominates the parent, it replaces the parent in the current population. If the parent dominates the candidate, the candidate is discarded. Otherwise, if the candidate and its parent are incomparable, the candidate is added to the population. After constructing candidates for each parent individual in the population, the population has possibly increased. In this case, it is truncated to the original size using nondominated sorting and crowding distance metric (as in NSGA-II [5]). This steps are repeated until a stopping criterion is met.

DEMO is a simple but powerful algorithm, presented in detail in [15]. From the three proposed algorithm variants, the elementary one, called DEMO/parent, is used in this work.

5 Optimization Experiments

5.1 Experimental Setup

Numerical experiments in multiobjective optimization of the casting process were performed for a selected steel grade with the slab cross-section of 1.70 m × 0.21 m. Candidate solutions were encoded as 18-dimensional real-valued vectors, representing water flow values at the center and corner positions in 9 zones of the secondary cooling area. Search intervals for cooling water flows at both center and corner positions in zones 1, 2 and 3 were between 0 and 50 m^3/h, while in the zones 4–9 between 0 and 10 m^3/h. Table 1 shows the prescribed target slab surface temperatures. The target value for the core length $l^{\mathrm{core}*}$ was 27 m, while its maximum deviation allowed $\Delta l^{\mathrm{core}}_{\mathrm{max}}$ was 7 m.

Table 1: Target surface temperatures in °C.

Zone number	Center position	Corner position
1	1050	880
2	1040	870
3	980	810
4	970	800
5	960	790
6	950	780
7	940	770
8	930	760
9	920	750

Four instances of the optimization problem were used in experiments, differing in the casting speed. The casting speed reflects the conditions under which the process needs to be conducted and significantly affects the productivity and product quality. In each problem instance the speed was kept constant, but at a different value. The values used were: 1.2 m/min, 1.4 m/min, 1.6 m/min and 1.8 m/min.

DEMO was integrated with the numerical simulator of the casting process into an automated optimization environment. DEMO evolved sets of candidate solutions in search for a good approximation set, and the simulator served as a solution evaluator. Steady-state operation of the casting machine was assumed and optimization performed in the off-line manner.

The most limiting factor for experimental analysis is the computational complexity of the casting process simulation. A single simulator run takes about 40 seconds on a 1.8 GHz Pentium IV computer. In initial experimentation we found DEMO runs with 5000 solution evaluations (and therefore taking about 55 hours) well compromising between the execution time and solution quality. Further algorithm settings were also adopted according to the initial parameter tuning experiments [6] and were as follows: population size 50, number of generations 100, scaling factor 0.5 and crossover probability 0.05. These settings ensure highly acceptable algorithm performance and repeatability of the results as indicated by the hypervolume measure [16] and attainment surface plots [12] obtained over five test runs of the algorithm and shown in Figs. 1–2.

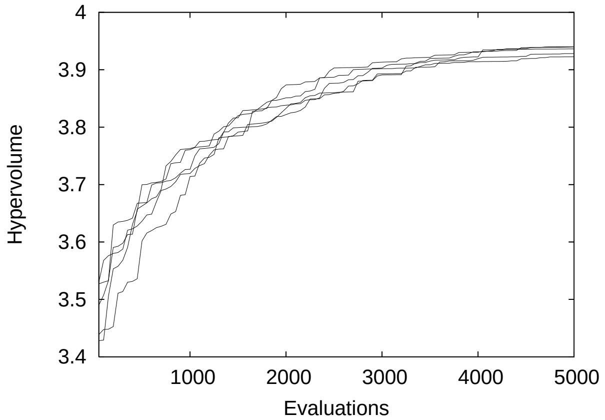

Figure 1: Hypervolume values in five test runs of the DEMO algorithm.

5.2 Results and Findings

The key result of this study were approximation sets of Pareto optimal fronts. Figure 3 shows the approximation sets found by DEMO for five casting speeds, ranging from 1.2 m/min to 1.8 m/min. Each set of nondominated solutions is the final result of a single DEMO run at a constant casting speed.

It can be observed that the two objectives are really conflicting in the sense that finding a minimum for one of them the optimization procedure fails to do so for the other and vice versa. It is also obvious that the casting speed has a decisive impact on the result. Moreover, the higher the casting speed, the more the two objectives can be met simultaneously. This corresponds with practical experience on the considered casting machine, where the process is easier to

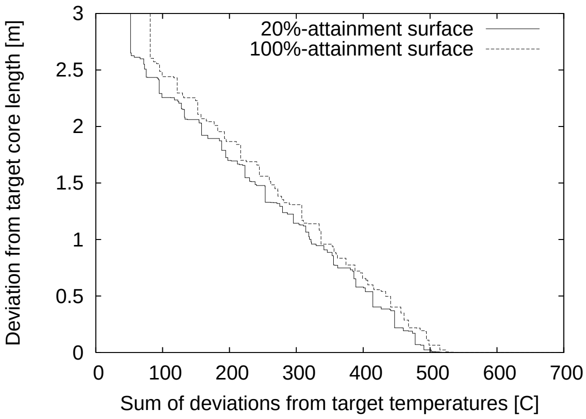

Figure 2: 20% and 100% attainment surfaces for the solutions found in five test runs of the DEMO algorithm.

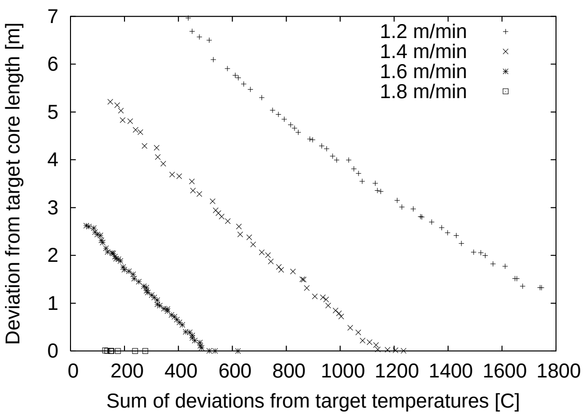

Figure 3: Nondominated solutions found with DEMO for different casting speeds.

control at the usual casting speed (1.6–1.8 m/min). Lower casting speed is clearly shown as disadvantageous and in practice it is only set exceptionally, for example, when a new batch of steel is awaited.

A detailed analysis of the solution properties also reveals that, in view of the objective c_1, the majority of actual surface temperatures are higher than the target temperatures, while regarding c_2, the actual core length is almost always shorter than the target value.

Looking into decision space, one can also observe certain regularities. In case of applying trade-off solutions from the middle of the approximation sets, the amount of coolant spent increases with the casting speed (see the left-hand side diagrams in Figs. 4–7). This is an expected result as higher casting speed implies more intense cooling. On the other hand, the distributions of temperature differences across the secondary cooling zones (right-hand side diagrams in Figs. 4–7) exhibit two characteristics. First, the target temperatures are much more difficult to achieve at the center than in the corner slab positions. Second, the differences at the center are rather non-uniform. While some are close to zero, others reach up to 200°C at lower cast-

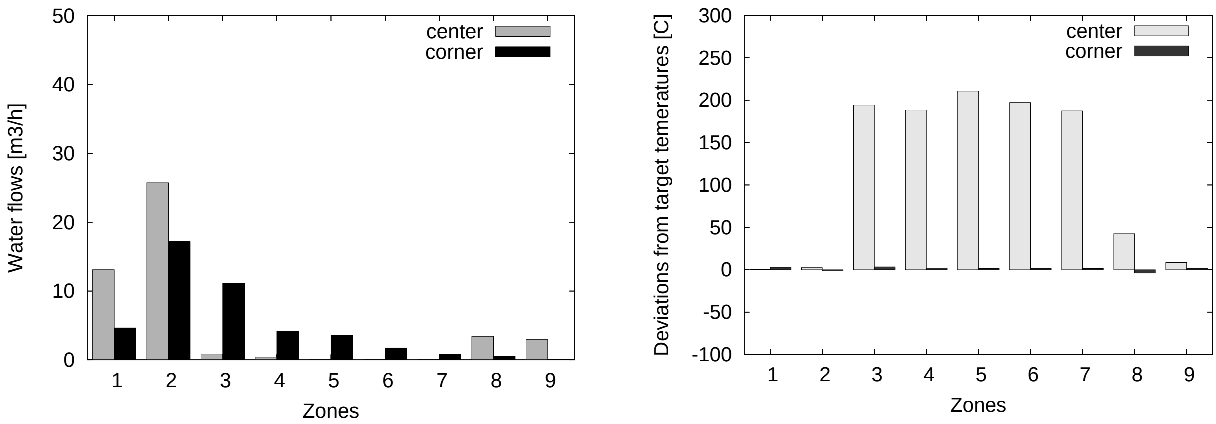

Figure 4: A trade-off solution from the middle of the approximation set for the casting speed speed of 1.2 m/min: c_1 = 1051°C, c_2 = 3.8 m.

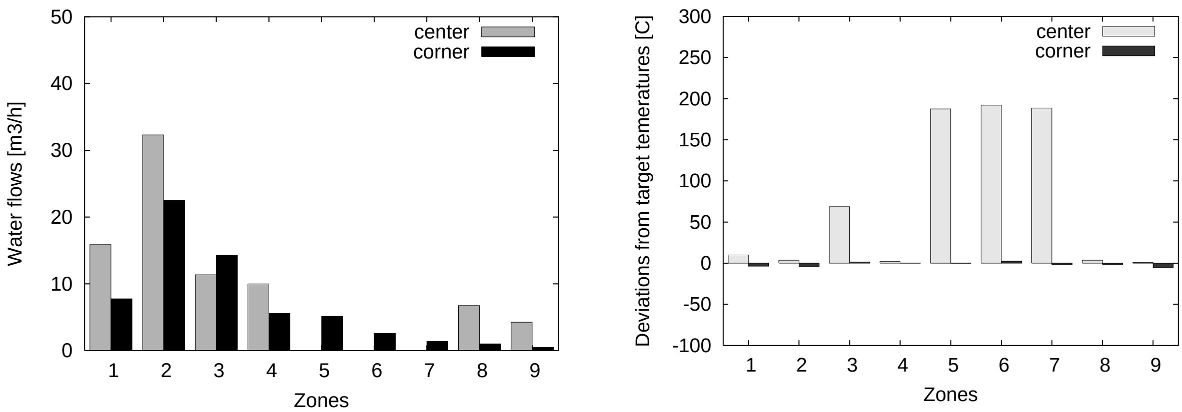

Figure 5: A trade-off solution from the middle of the approximation set for the casting speed speed of 1.4 m/min: c_1 = 677°C, c_2 = 2.2 m.

ing speeds. Such a situation is not preferred in practice and calls for the reformulation of objective c_1 in further calculations.

On the other hand, it is worth checking the extreme solutions from an approximation set at a given casting speed. Figures 8 and 9 clearly show how one objective is met at the expense of the other. None of these would normally be used in practice. Instead, a plant engineer would rather select a trade-off setting balancing between the two objectives.

6 Conclusion

Advanced manufacturing and processing of materials strongly rely on numerical analysis of the related processes made possible by powerful modeling and simulation software packages. To use them efficiently, an upgrade is needed towards process automatic optimization. The optimization environment studied in this paper consists of a numerical process simulator and an evolutionary multiobjective optimization algorithm. We illustrated the capabilities of this approach in process parameter optimization in continuous casting of steel. Solving this task successfully is a key to higher product quality.

In the preliminary study of optimizing 18 cooling water flows with respect to two objectives on an industrial casting machine the capabilities of the multiobjective problem treatment were shown. The analysis assumes steady-state process conditions, hence the results are not primarily intended for control purposes but rather for better understanding of the process and evaluation of the casting machine performance. The resulting approximation sets of Pareto optimal fronts indeed offer a more general view of the process properties. The results support some facts already known in practice and, at the same time, show critical points, such as the need to reformulate the temperature deviation criterion to ensure uniform distribution of temperature differences over the zones, and extend the optimization problem definition with an additional constraint. From the practical point of view, further studies will also explore

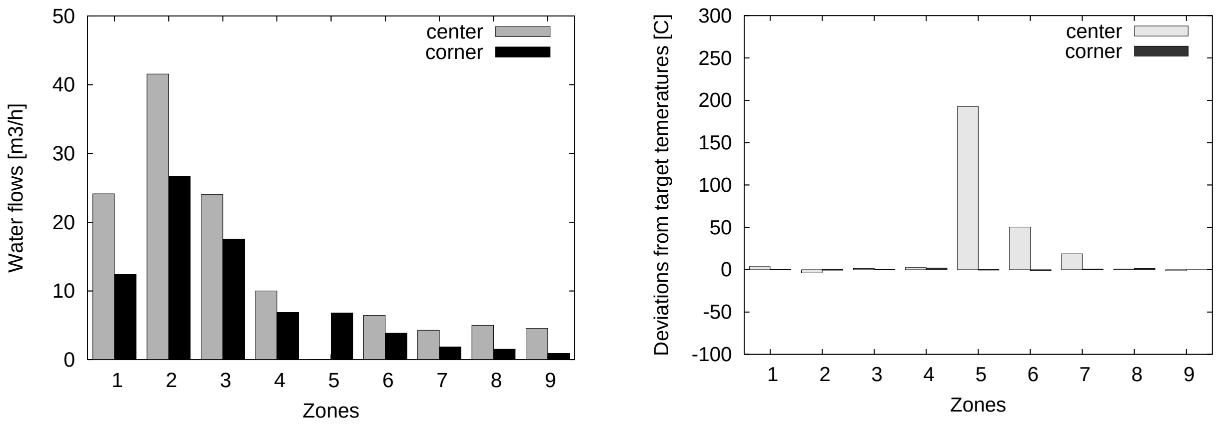

Figure 6: A trade-off solution from the middle of the approximation set for the casting speed speed of 1.6 m/min: c_1 = 281°C, c_2 = 1.3 m.

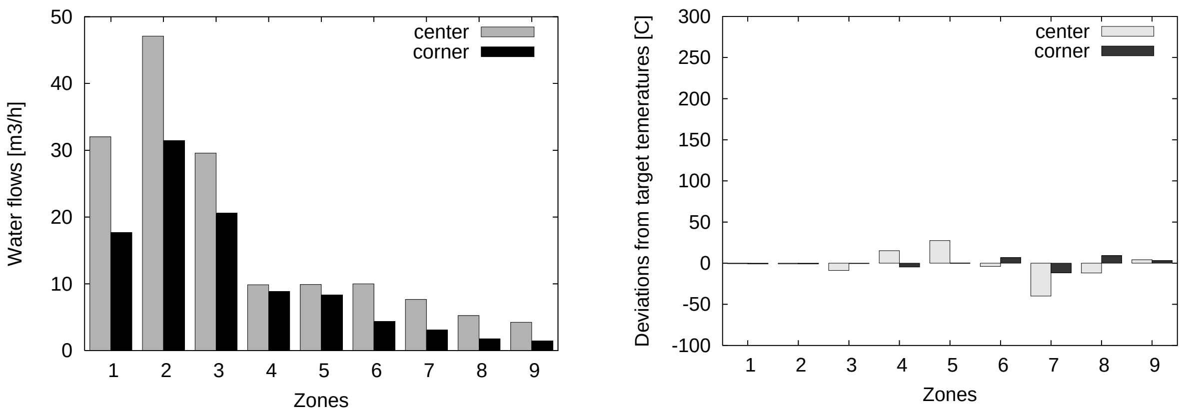

Figure 7: A trade-off solution from the middle of the approximation set for the casting speed speed of 1.8 m/min: c_1 = 151°C, c_2 = 0.0 m.

how much the optimization results are affected by the factors that were kept constant so far, such as steel grade, slab geometry and casting machine characteristics.

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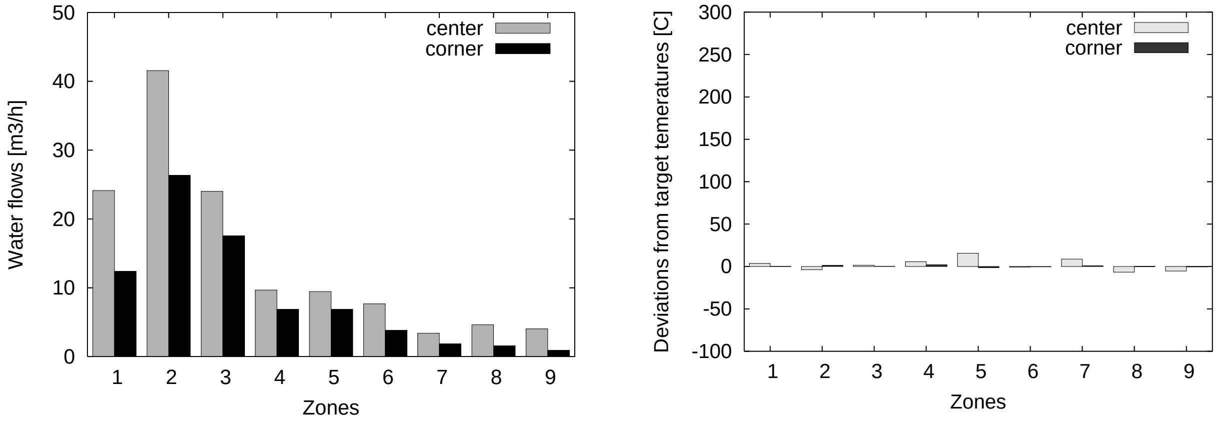

Figure 8: The leftmost solution from the approximation set for the casting speed speed of 1.6 m/min: c_1 = 58°C, c_2 = 2.6 m.

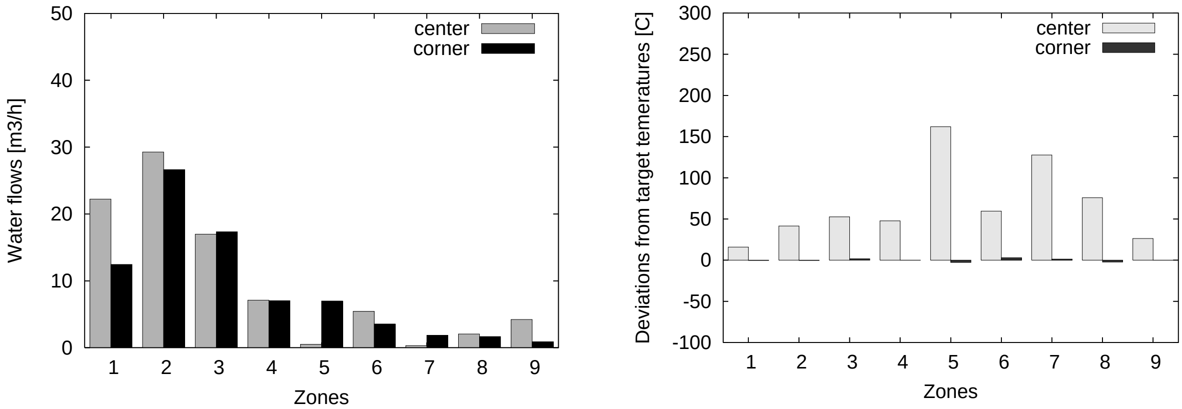

Figure 9: The rightmost solution from the approximation set for the casting speed speed of 1.6 m/min: c_1 = 620°C, c_2 = 0.0 m.

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